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ARTIFICIAL NEURAL NETWORK MODELLING OF THE ENERGY CONTENT OF MUNICIPAL SOLID WASTES IN NORTHERN NIGERIA

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Abstract
The study presents an application of the artificial neural network model using the back propagation learning algorithm to predict the actual calorific value of the municipal solid waste in major cities of the northern part of Nigeria, with high population densities and intense industrial activities. These cities are: Kano, Damaturu, Dutse, Bauchi, Birnin Kebbi, Gusau, Maiduguri, Katsina and Sokoto. Experimental data of the energy content and the physical characterization of the municipal solid waste serve as the input parameter in nature of wood, grass, metal, plastic, food remnants, leaves, glass and paper. Comparative studies were made by using the developed model, the experimental results and a correlation which was earlier developed by the authors to predict the energy content. While predicting the actual calorific value, the maximum error was 0.94% for the artificial neural network model and 5.20% by the statistical correlation. The network with eight neurons and an R^2 = 0.96881 in the hidden layer results in a stable and optimum network. This study showed that the artificial neural network approach could successfully be used for energy content predictions from the municipal solid wastes in Northern Nigeria and other areas of similar waste stream and composition.

Keywords: Artificial Neural Network, back propagation learning algorithm, municipal solid waste, northern Nigeria, calorific value.

1. Introduction

Accurate prediction of municipal solid waste's (MSW) quality and quantity is crucial for designing MSW management system. The prediction of the amount of waste to be generated is a difficult task because various parameters affect it and its fluctuation is high (Jalili and Noori, 2008; Elmira *et al*., 2011). The thorough implementation of waste management policies across the world and particularly in Nigeria is faced with many obstacles; one of which is the lack of information and lack of understanding of the key factors contributing to waste generation. Factors such as population, personal income, migration rates, literacy level and waste composition were identified as some of the most important factors representing socio-economic conditions contributing to waste generation. The recognition, identification and understanding of these factors is essential for implementing waste management policies to reduce the amounts of waste generated or the choice of a better and optimum treatment method.

The capability of the artificial neural network (ANN) to learn and at the same time generalize the relationship among data sets and give satisfactory and quick estimations has made it more attractive for many engineering applications. The ANN offers the ability to handle large amount of data sets, ability to implicitly detect complex nonlinear relationships between dependent and independent variables, ability to detect possible interactions between predictor variables.

In recent years, many field of engineering have applied ANN and favourable results were produced. Some of the applications include photovoltaic system sizing (Mellit and Kalogirou, 2008; Mellit *et al.*, 2009),lighting and space cooling energy consumption (Aydinalp *et al.*, 2002), estimation of solar radiation (Dorvlo *et al.*, 2002),refrigeration system (Hosoz and Ertunc, 2006.), automobile air conditioning system (Hosoz and Ertunc, 2006; Rosiek and Batlles, 2010), heat transfer processes (Balcilar *et al.*, 2011), prediction of biogas generation from anaerobic digestion (Tomaž and Miran, 2010) and waste management (Eduardo *et al.*, 2004; Kurtulus *et al*., 2006; Samira and Hoo, 2013; Qeethara and Ghaleb, 2013; Sharif *et al.*, 2013; Elmira *et al.*,

2014; Liliana, 2014). Furthermore, other energy related problems have also been solved using ANN approach (Kalogirou, 2000; Kalogirou, 2001).

Adamovic *et al.* (2017) went further to develop a general regression neural network (GRNN) model for the prediction of annual municipal solid waste (MSW) generation at the national level for 44 countries of different size, population and economic development level. Proper modelling of MSW generation is essential for the planning of MSW management system as well as for the simulation of various environmental impact scenarios. The main objective of their work was to examine the potential influence of economic crisis (global or local) on the forecast of MSW generation obtained by the GRNN model. The existence of the so-called structural breaks that occur because of the economic crisis in the studied period (2000-2012) for each country was determined and confirmed using the Chow test and Quandt-Andrews test. The novelty of the applied method was that it used broadly available social, economic and demographic indicators and indicators of sustainability, together with GRNN and structural break testing for the prediction of MSW generation at the national level.

Ogwueleka and Ogwueleka (2010) applied a feed forward ANN trained by error back propagation algorithm to predict the lower heating value of MSW in Abuja, Nigeria. Components such as plastic, paper, glass, textile and food were found to be essential for prediction of lower heating value of the MSW. The authors used 60 dataset divided into 37 training dataset and 23 validating dataset**,** gathered from Abuja waste stream, artificial neural network was trained and validated. Their model provided the best fit and the predicted trend followed the observed data closely; the determination coefficient for training and validating dataset were 0.992 and 0.981, respectively.

This paper presents the application of the ANN for predicting the energy content of MSW in Northern Nigeria from its composition. The back propagation (BP) learning algorithm would be used.

2. Materials and Methods

2.1 Study area

Major cities of the northern part of Nigeria, with high population densities and intense industrial activities constitute the area of study. These cities are: Kano, Damaturu, Dutse, Bauchi, Birnin Kebbi, Gusau, Maiduguri, Katsina and Sokoto in Kano, Yobe, Jigawa, Bauchi, Kebbi, Zamfara, Borno, Katsina and Sokoto states respectively.

2.2 Materials

Experimental data of the energy content of the municipal solid waste (MSW) in Northern Nigeria for the present study are taken from Oumarou *et al.*, (2016). The physical characterization of the MSW which serve as the input parameter were wood, grass, metal, plastic, food remnants, leaves, glass and paper. They were presented in varying proportions in all waste samples in the study area. Table 1 shows the data from which the ANN model was generated.

Table 1: Energy contents of the municipal solid waste (Oumarou *et al.*, 2016).

Locality	Components (%)								
	Wood (a)	Grass (b)	Paper (c)	Leaves (d)	Food remnants (e)	Plastic (f)	Metal (g)	Glass (h)	Actual Calorific value (MJ/kg)
Kano	28.46	6.57	9.66	8.92	6.79	18.99	12.58	8.00	5.667
Damaturu	16.62	11.48	3.58	16.24	6.03	38.20	3.64	4.21	5.345
Maiduguri	27.28	5.59	6.69	13.17	6.17	32.56	2.94	5.599	5.078
Dutse	19.04	5.73	11.34	19.14	5.94	23.93	6.46	8.39	5.277
Bauchi	22.28	6.29	14.86	13.83	5.12	24.93	7.80	4.87	5.379
Katsina	24.75	6.05	10.52	15.57	4.35	20.46	9.76	8.54	5.476
Sokoto	20.07	5.02	8.82	8.54	6.88	17.63	15.85	7.35	5.362
Gusau	17.99	17.11	8.18	14.99	8.03	16.27	10.73	6.70	5.164
BirninKebbi	19.78	5.35	9.82	5.48	5.98	34.58	12.96	6.04	5.494

In developing an ANN model, the available data set is divided into two sets, one set to be used for training the network (70–80% of the data) and the other set to be used to verify the generalization capability of the network (Aydinalp *et al.*, 2001). The inputs were wood (a), grass (b), metal (c), plastic (d), food remnants (e), leaves (f), glass (g), and paper (h), percentage compositions and the outputs is the actual calorific value. Input–output pairs are presented to the network, and the weights are adjusted to minimize the error between the network output and the actual value. Once training is completed, predictions from a new set of data may be done using the already trained network.

2.3 Artificial Neural Network (ANN) Modelling

ANNs are an attempt at modelling the information processing capabilities of the brain and nervous systems. The brain consist of large number (approximately 10^{11}) of highly connected elements (approximately 10^4 connections per element) called neuron. Each neuron consists of three components –dendrite, cell body and axon. The dendrite (input unit) receive electric signal and pass it to cell body (processing unit) that process the signal and pass the processed signal to other neuron through the axon (output unit). The ANN is analogous to the biological neural network whereby the network is trained by some set of input and the associated output data. After the training, another set of input data are used to predict the output with the hope that during the training, the neurons has learned the relationship between the input and output data (error between the output and target is minimal). A typical example of an architectural neural network that consists of the three major layers (input, hidden and output) is shown in Figure 1. The number of hidden layer may be varied which can improve the predictive capability of the network.

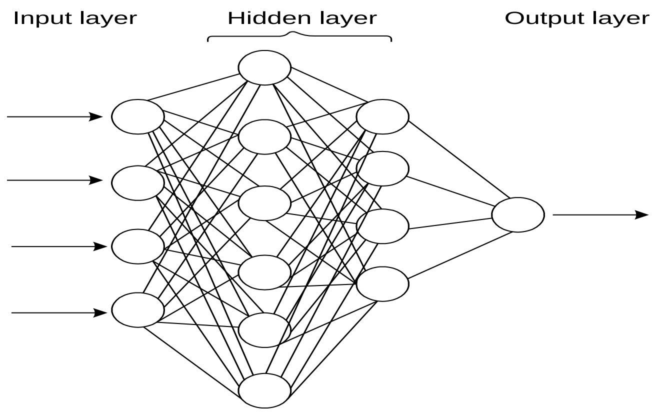

Figure 1: Schematic diagram of a multi-layered ANN

The number of input parameter must be equal to the number of input layer. Likewise, the output parameter must also be equal to the output layer.

The inputs (X) into a neuron are multiplied by their corresponding connection weights (W), summed together and a threshold (θ), acting at a bias, is added to the sum. This sum is transformed through a transfer function (f) to produce a single output (h), which may be passed, on to other neurons. The function of a neuron can be mathematically expressed as

$$h = f(\sum WX - \theta), \qquad (1)$$

Where the transfer function (f) of the neuron is the sigmoid activation function, being in the present work given as

$$f(x) = \frac{1}{1 + e^{-x}} \qquad (2)$$

In this study, back propagation (BP) algorithm is used to train the network because it has been proven that BP with appropriate number of hidden layer, can successfully model any nonlinear relation to high level of accuracy (Pacheco-Vega *et al.*, 2001). The purpose of BP is to reduce the error between the output and the target to higher level.

The proposed algorithm in this study was developed and solved using MATLAB 7.12.0.635 (2011a).

In order to facilitate the comparisons between predicted values and experimental values, an error analysis, has been done using Mean Square Error (MSE) and the absolute fraction of variance (R^2). The MSE is given by:

$$MSE = \frac{1}{n}\sum_j (t_j - o_j)^2 \qquad (3)$$

and the R^2 is given by

$$R^2 = 1 - \frac{\sum_j (t_j - o_j)^2}{\sum_j (o_j)^2} \qquad (4)$$

Where t_j is actual values, o_j is the predicted (output) values and *n* is the number of the data.

3. Results and Discussion

The purpose of applying the ANN model and considered BP learning algorithm is to assess the capability of the ANN to predict the energy contents, the actual calorific value (ACV) of the municipal solid waste. The network has eight input parameters, wood (a), grass (b), metal (c), plastic (d), food remnants (e), leaves (f), glass (g), and paper (h), percentage compositions and the outputs is the ACV (energy contents). These inputs were later grouped into four major parameters.

The model ability to predict well was observed for different numbers of hidden layer nodes starting from 2, 4, 6, 8 and 10 neurons. There is no specific criterion for choosing the number of hidden layer. A specific problem will determine the choice of hidden layer size and the quality of training patterns. Also, an adequate number of neurons that will give optimum performance ensure generalization must be selected. If the number of neuron selected is not enough, then, the network will not learn correctly and if too much, there will be over fitting.. Some researchers are of the opinion that the upper bound of the number of neurons in the hidden layer should be one more than twice that of the number of input units. However, this method does not assure generalization of the network (Rafig *et al.*; 2001). Thus, ANN problem requires some little trial and error to set up an appropriate and stable network for the problem.

In order to design a stable ANN, the number of neurons in the hidden layer was varied so that the stability of the network could be tested. The criteria used to measure the network performance were absolute fraction of variance (R^2) and mean square error (MSE). The MSEs for two neurons, four neurons, six neurons, eight neurons and ten neurons in the hidden layers are 1.459×10^{-3}, 9.459×10^{-4}, 5.314×10^{-4}, 4.377×10^{-5} and 2.171×10^{-2} respectively. From these errors, the network with eight neurons gives the least error, hence, the best network. To further confirm the network performances, the absolute fraction of variance (R^2), were also determined for the various networks. Figures 2 -6 show the R^2 of the network with various numbers of neurons in the hidden layer. Comparing these entire Figures 'R^2,the network with eight neurons (R^2=0.96881) in the hidden layer results in a stable and optimum network (Figure 5).These results further confirmed that network with eight neurons gives optimum network performance.

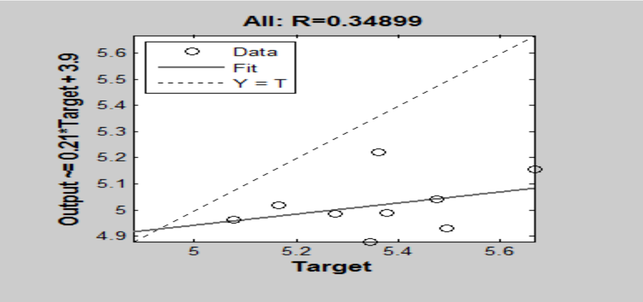

Figure 2: The network performance with **two** neurons in the hidden layer

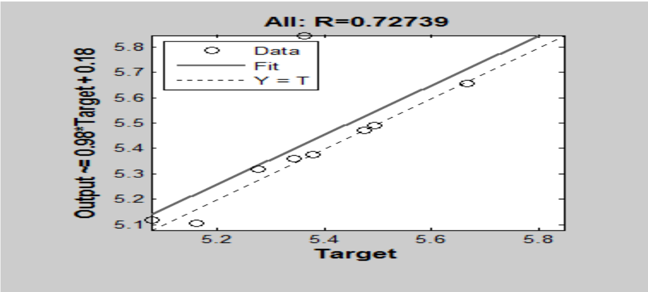

Figure 3: The network performance with **four** neurons in the hidden layer

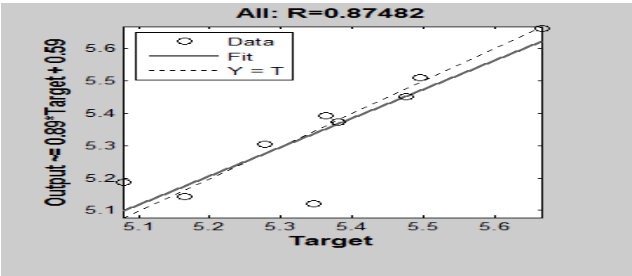

Figure 4: The network performance with **six** neurons in the hidden layer

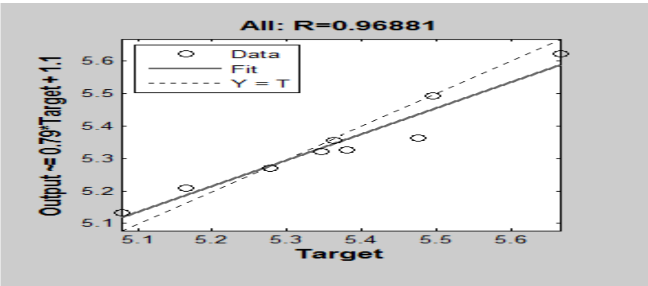

Figure 5: The network performance with **eight** neurons in the hidden layer

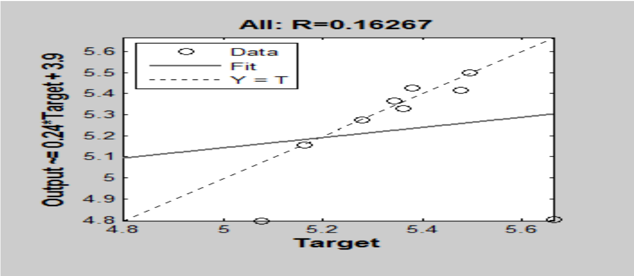

Figure 6: The network performance with **ten** neurons in the hidden layer

To decide upon the ability of the network proposed in the prediction of the parameter mentioned, comparative presentations were made by using the correlation (Eq. 5) originally developed by Oumarou *et al.*, (2016).

$$\mathrm{ACV} = 1.0325 - 0.0011\mathrm{a} + 0.2254\mathrm{b} - 0.0046\mathrm{c} - 0.0068\mathrm{d} + 0.3184\mathrm{e} - 0.0119\mathrm{f} - 0.0053\mathrm{g} + 0.1099\mathrm{h} \quad (5)$$

While predicting the actual calorific value, the maximum error was 0.94% for the ANN model and 5.20% by the statistical correlation. The network with eight neurons (R= 0.96881) in the hidden layer results in a stable and optimum network (Fig. 5). These results further confirmed that network with eight neurons gives optimum network performance. These results show that artificial neural network is an effective tool in forecasting energy content. Thus the proposed ANN model can be a viable alternative for a more accurate prediction of MSW generation in northern Nigeria. It could constitute a basis for the development of a model at the national level. It is non-parametric model and easy to use and understand compared to statistical methods.

Table 2 shows the comparison of the experimental values of the actual ACV (energy content), those predicted using the correlation (Eq. 5) (Oumarou *et al.;* 2016) and those predicted using the best ANN configuration. As confirmed by Ogwueleka and Ogwueleka (2010), the lower heating value has indeed strong relationship with the composition of the MSW.

Table 2: Comparison of the experimental values of the actual calorific value, those predicted using correlation and those predicted using ANN configuration.

Locality	ACV (MJ/kg) (Expt.)	Predicted ACV (MJ/kg)[13]	Predicted ACV (MJ/kg) (ANN)
Kano	5.667	5.1255	5.6605
Katsina	5.345	5.3837	5.3410
Maiduguri	5.078	4.3191	5.0771
Damaturu	5.277	4.6152	5.2762
Dutse	5.379	4.0908	5.3772
Bauchi	5.476	4.2431	5.4826
Gusau	5.362	4.7479	5.3564
Sokoto	5.164	7.7724	5.2150
Birnin Kebbi	5.494	7.9444	5.4854

4. Conclusion

From the results obtained, the following conclusions were drawn:

1. The predicting capability of the ANN model is better than that of the correlation which was developed earlier by the authors.
2. The ANN model could be considered as a substitute and practical method of evaluating the actual calorific value from the municipal solid waste.

3. Even though this method may be time consuming to develop the best network, it is realistic due to its capability to learn and generalize the data set with a wide range of experimental conditions.

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